3D REGISTRATION BASED ON ICP ALGORITHM AND SIGINFICANT CRITICAL POINTS

O. M. ElBakry[1], A. M. El-Bialy[1],A. H. Kandil[1], S. A. Fawzy[1], Y. A. Mostafa[2] , A.R. El_Beialy[2]
[1] Systems and Biomedical Engineering Department, Cairo University, Giza, Egypt
[2] Department of Orthodontics, Oral and Dental Medicine, Cairo University, Giza, Egypt
e-mail: o.elbakry@k-space.org

Abstract- **This work is concerned with the development of a new method for the registration of three-dimensional (3D) objects. It is based on the iterative closest point (ICP) algorithm. To reduce the processing time, the previous work focused on the improvement of the ICP algorithm. However, in this work, a different approach has been followed for the improvement of the registration performance. This is accomplished by applying the ICP algorithm only on some chosen (critical) points instead of applying it to the whole point set. This approach significantly improves the time needed for initial registration. Different criteria have been applied to determine the critical points which results in different registration accuracy. The results have shown that the one with the highest performance is the method based on the principle curvatures calculation. Such a method has reduced the processing time by more than 90%, while preserving almost the same accuracy.**
Keywords - **Registration, ICP, Critical points**

I. Introduction

Registration and matching techniques have applications in many areas such as object recognition, motion estimation, scene understanding and various applications in the medical field. Registration techniques are used in stereo-tactic surgery and the comparison of pre-operative and post-operative images to demonstrate the progress of the patients' treatment plan [1].

Many methods are proposed to tackle the surface registration problem. One of the main methods for surface registration of two objects is to create signature images [9-12]. By finding the correspondence between these images, the registration parameters (rotation and translation) are calculated. Another important method is to use directly the original point sets of each object. The most common and most important technique in this method is the iterative closest point (ICP) algorithm [2]. In this approach, an exhaustive search is performed to match the closest points. Although, the registration results were accurate, the processing time was long. To overcome this drawback some modifications have been developed for the ICP algorithm [3-8,15-16]. These modifications affect all the phases of the algorithm from the selection and matching of points to the minimization strategy. Instead of the exhaustive search for the closest points, the search is done using k-D tree (k-dimensional binary search tree) [3, 5]. In [8], a neighborhood within a certain distance ϵ is calculated for each point $\vec{p}_j$ in the reference set P. The preprocessing is done using k-D tree. The points within each ϵ-neighborhood are sorted according to the distances to the corresponding $\vec{p}_j$. After being sorted, the Triangle and Spherical constraints are introduced .The Spherical constraint is applied to determine if the nearest neighbor falls within its correspondence neighborhood determined at the previous iteration. Then, the Triangle constraint and the Ordering theorem are applied to this neighborhood. The main idea of the Ordering theorem is to arrange the points by increasing distance to each point. Any point that violates the Triangle constraint is discarded with its subsequent points. Both Collinearity and Closeness constraints are introduced in [7] to improve the search.

The coarse to fine strategy is introduced in [3- 5]. In this strategy, the points are divided into hierarchical structure according to their resolution. Every 2^h-th data point is considered as a control point, where $h + 1$ is the number of hierarchical levels. After the convergence of the registration algorithm for one set of control points, the computation is continued on the next hierarchical level. For large point sets, the coarse to fine strategy considerably speeds up the computation time. Modifications in the distance metric used and the objective function to be minimized are also presented [3, 4, 6]

This work is mainly concerned with choosing critical points, on which the ICP algorithm is applied to calculate the motion required. So, the time needed is reduced while preserving both efficiency and robustness of the ICP algorithm.

The organization of the paper is as follows. Section two describes the different methods used on which the critical point selection is done. The experimental results of each method are presented in section three. Section four concludes the paper with a brief discussion.

II. Methodology

Generally, the research in this area focused on improving the ICP for the sake of better performance and shorter execution time. In this work, a new algorithm is developed to select critical points that will be used for initial registration. This will reduce the problem domain. Consequently, this will save both the processing time and the computational effort. In all the methods presented, after selecting the critical points, the ICP algorithm is applied only on these points. The motion estimation computed using these critical points from the previous step is then applied to the whole object.

A. Point selection based on distance histogram

A new approach, to roughly register the two objects, is to generate a distance histogram for each one. This is achieved by computing the Euclidean distance between the object center of gravity and all the mesh points, then generating a histogram for the various distances. From the similarity

conditions of the two histograms, points are chosen to compute the motion required to register the two objects.

This approach can be summarized as follows:

1- Compute the Euclidean distance between each face of the mesh and the center of gravity of the whole object.

2- The number of points existing at every distance value are computed and used to generate the distance histogram. The resulting histogram is spread over a large scale of distances with the number of points is very sensitive to outlier points. To overcome this problem, the range of distances is divided over a limited scale of regions. This histogram quantization is required to be dense enough, to be less sensitive to noise and not too dense to preserve the characterizing shape of the histogram. This approach is tested for different scales. It reduces the number of critical points and the execution time required, while the registration accuracy is preserved. The results of scale division over 100 and 200 regions are shown in table 1.

3- Locate the maximum region in the histogram. Select its corresponding points as the critical points for each object.

Fig. 1 shows how the distances of meshes' points relative to the center of gravity are calculated at spherical regions.

B. Point Selection based on Neighborhood angle conditions

For each triangular facet in the given mesh, as shown in fig. 2, the angle is measured between it and the neighboring facets. A neighbor facet must be connected and not just within a predefined distance limit. The angle measurement is the relative angle between the facet normals, thus ensuring that the angle measured between neighbors is invariant to rigid transformations. The maximum angle between a facet and its neighbors is computed. The centers of gravity of all facets having this maximum angle relative to their neighbors are marked as the required critical points.

Relative angle information and relative distance information used to be encoded in signature images created at certain points [9-12, 14]. This work modifies the previous approaches to determine the critical points. In this research work, the distance histogram measures and the relative angle measures are used directly to mark critical points that are introduced to the ICP algorithm.

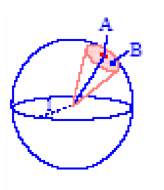

Fig. 1 Calculating distances of meshes facet at different sphere sizes

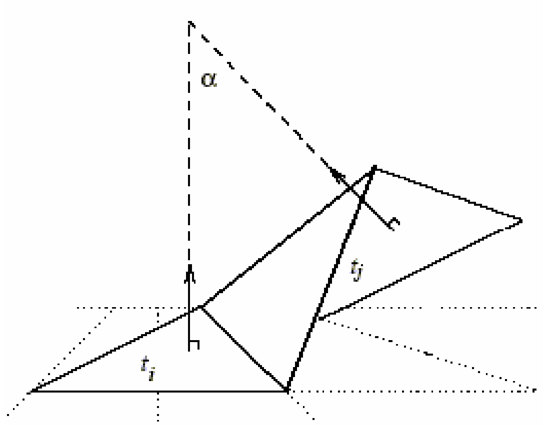

Fig. 2 The relative angles measured

C. Point Selection based on Principle curvature

As shown in fig. 3, any smooth surface S has an infinite set of normal curvatures around point p in every direction [17,18]. The orientation of *S* at *p* is specified with the unit-length normal *N*. A plane Π_p that contains p and N can be constructed, and the intersection of Π_p with S forms a contour α on S. *T* is the unit-length tangent vector at *p*. Π_p is not a unique plane, if Πp is rotated around N a new contour on S with its normal curvature is formed. There is an infinite set of these normal curvatures around p in every direction. For this infinite set an orthonormal basis that completely specifies the set is constructed (*principal curvatures*) which is chosen as the tangent vectors $\{T_1, T_2\}$ associated with the maximum and minimum normal curvatures at p since the directions of these curvatures are always orthogonal. The maximum and minimum normal curvatures at p are considered as the *principal curvatures* (k_1, k_2)

The curvatures k_1 and k_2 associated with these directions for any normal curvature at p:

$$k_p(T_\theta)=k_1 \cos^2(\theta) + k_2 \sin^2(\theta) \qquad (1)$$

Where $T_\theta = T_1 \cos(\theta) + T_2 \sin(\theta)$,

and $-\pi \leq \theta < \pi$ is the angle to vector T_1 in the tangent plane.

The principal directions along with the principal curvatures completely specify the surface curvature of S at p .

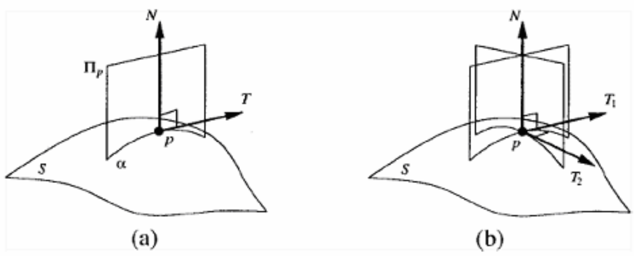

Fig. 3 a-A normal curvature on the surface S at the point p, b- The principal directions {T1,T2}

The gaussian curvature (K) is the product of the principal curvatures and the mean curvature (H) is the average sum of both principal curvatures

The Shape Index(SI) is a quantitative measure of the shape of a surface at a point *p*, is defined as

$$SI = \frac{2}{\pi}\arctan\frac{k_2 + k_1}{k_2 - k_1} = \frac{2}{\pi}\arctan\frac{H}{\sqrt{H^2 - K}} \qquad (2)$$

Every distinct surface shape corresponds to a unique value of SI, except the planar shape. Points on a planar surface have an indeterminate shape index, since $k_1 = k_2 = 0$.

In [13] critical points (extremal points) of the 3D surfaces are presented. The extremal points were defined as the extremum of principal curvatures within volumetric data The scalar measurements used in the matching included the type of extremal point, which depends on the sign of the principal curvatures, the principal curvature values, and the distances and orientations of vectors to neighboring points. It was shown that the relative positions of those points are invariant to 3D rotation and translation.

In this work, we search for the points that their SI corresponds to convex or concave shapes and are then marked as the critical points needed. The Gaussian and mean curvatures for all the object points are calculated.

D. Iterative Closest Point(ICP) Algorithm

This iterative algorithm [2] has three basic steps to register two objects defined as two point sets P and M:

1. Pair each point of P to the closest point in M. Search will be done to compute each point and its corresponding closest point. The distance computed between any two points is an Euclidean distance.
2. Compute the motion that minimizes the mean square error (MSE) between the paired points with respect to the six rotation and translation parameters. For yielding the least squares rotation and translation the quaternion-based algorithm is used.
3. Apply the motion to data set points P and update the MSE.

The three steps are iterated. The iterations are terminated when the change in MSE falls below a preset threshold or the number of iterations exceeds a preset value. The iterations have been proved to converge in terms of the MSE

III. Results

The main ICP algorithm after selecting the critical points based on the different three methods and the results of registration due to these methods are compared to applying ICP directly on all the points of the given data sets.

The four registration algorithms, described in the previous section, have been evaluated using many point sets of different skulls. The size of the point sets range from 20000 points to over 30000 points.

Table 1 presents the computation times and the mean square error (MSE) determined using different point sets. All

TABLE 1: THE RESULTS OF THE DIFFERENT METHODS USED

Method used	Number of points	MSE	Exec. Time (seconds)
ICP alone	24850	0.000668	240
Distance Histogram (scale 100 points)	841	0.000318	114.6
Distance Histogram (scale 200 points)	449	0.0422	40
Neighborhood angle condition	201	0.01167	19.4
Principle curvatures	268	0.000133	9.7

computation times and MSE have been averaged over many trials with different initial rotations and translations.

The first iteration of the algorithm always translates the data point set so that its center of mass coincides with that of the model point set, due to the least squares quaternion operation defined in the original ICP algorithm.

An example of the registration results of two skulls using the approach based on principle curvatures is shown in fig. 4.

IV. Conclusion

In this paper we have presented a method for robust registration of 3-D point sets especially that of the skull point sets that are characterized by very large number of points. The critical points of each object are determined using the algorithms described in section two. Based on these points, the motion parameters are computed using ICP algorithm. A set of experiments have been conducted to compare and to evaluate the three algorithms. When compared to the original ICP algorithm, the critical points' approach developed in this paper has shown considerable time reduction with the preservation of efficiency.

The distance histogram method depends on choosing the points in one region, the region with maximum points. So, this may cause, in some situations, inaccurate results , because of the dependence on one region. To overcome this problem, the points of another region other than the maximum one are additionally used. However, this solution significantly increases the computational time.

Fig. 4 Registration results of two skulls

The main drawbacks of the distance histogram method, are its sensitivity to the number of regions selected and its dependence on the scale used.

It is shown in table 1 that the principle curvature method gives the minimum execution time and the best registration efficiency. The average number of points was reduced from the original number 24850 to about 268, i.e. the points used are about 1% of the original number of points. Thus, the time needed is reduced from 240 seconds to 9.7 seconds, meaning a reduction to about only 4% of the original time needed preserving the robustness of the algorithm (even less average MSE). On the other hand, the time reduction in previous research work dealing with modifying the algorithm itself did not show this time reduction. The picky algorithm [5] succeeded in reducing time to 72% of the original time ,where in [15] time is reduced to 33%, in [3] it was reduced to 90%, in [4] time decreased to 28% and in [16] it was reduced to 8.33%.

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